

## **Assignment - 2**

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Session : 2019-2020  
Course : Neural Network and Deep Learning  
Course Code : CSE4261  
Dept : Computer Science and Engineering  
Date : 27-05-2025

Below shows the activation function list for every model that they were used for building their architecture and also shows the accuracy after using the different activation functions in the head:

<b>Model</b>	<b>Activation Function Used</b>	<b>Accuracy after using ReLu in head</b>	<b>Accuracy after using Softmax in head</b>
MobileNetV2	ReLu6	15.95%	69.80%
ResNet50	ReLu	6.45%	5.65%
VGG16	ReLu	8.95%	25.80%
EfficientNetB0	Swish	5.00%	5.00%
DenseNet121	ReLu	9.20%	66.05%
NASNetMobile	ReLu	24.05%	72.85%
EfficientNetV2B0	Swish	5.00%	5.00%
InceptionV3	ReLu	28.60%	74.85%
Xception	ReLu	47.25%	76.70%
InceptionResNet V2	ReLu	28.50%	79.30%

Here we can see that, if we use the activation function as a ReLu without softmax then the accuracy are decreased for those models.

Below shows the list of the CNN models those are used regular kernel, deformable kernel, dialated kernel, depthwise separable kernel, modified depthwise-separable kernel, and pointwise kernel

Kernel Types	CNN models
Regular kernel	VGG16, ResNet50, DenseNet121
Deformable kernel	Deformable ConvNet v1, Deformable ConvNet v2, YOLOv4
Dialated kernel	DeepLabv3, WaveNet, ESPNet
Depthwise separable kernel	MobileNetV1, Xception, EfficientNet
Modified Depthwise-Separable kernel	MobileNetV2, MobileNetV3, FBNet
Pointwise kernel	InceptionV3, ResNet (Bottleneck), MobileNet series

My chosen CNN model is InceptionResNetv2. Below breaking down the feature map evolution layer by layer for this architecture, focusing on how each layer transforms the input into higher-level representations.

### 1. Stem Block

- Input:  $224 \times 224 \times 3$  (ImageNet input size)
- Layers:
  - $3 \times 3$  Conv  $\rightarrow$  32 filters  $\rightarrow 149 \times 149 \times 32$
  - $3 \times 3$  Conv  $\rightarrow$  32 filters  $\rightarrow 147 \times 147 \times 32$
  - $3 \times 3$  Conv  $\rightarrow$  64 filters  $\rightarrow 147 \times 147 \times 64$
  - MaxPool + Conv  $\rightarrow 73 \times 73 \times 192$

Feature maps: Capture edges, gradients, color blobs. Low-level features.

### 2. Inception-ResNet-A Block (5x)

- Output:  $35 \times 35 \times 320$
- Each block contains:
  - Parallel branches ( $1 \times 1$ ,  $3 \times 3$ ,  $5 \times 5$  convolutions)
  - Concatenation + Residual shortcut

Feature maps: Learn mid-level patterns — corners, textures, basic shapes.

### 3. Reduction-A Block

- Downsamples to  $17 \times 17 \times 1088$

Feature maps: Begin learning object parts like heads, wheels, leaves.

### 4. Inception-ResNet-B Block (10x)

- Output:  $17 \times 17 \times 1088$
- Uses narrower filters (like  $1 \times 7$ ,  $7 \times 1$ ) to capture asymmetrical patterns.

Feature maps: Represent larger structures — faces, windows, animal parts.

### 5. Reduction-B Block

- Output:  $8 \times 8 \times 2080$

Feature maps: Now abstract enough to represent full objects — cars, dogs, etc.

### 6. Inception-ResNet-C Block (5x)

- Output:  $8 \times 8 \times 1536$

Feature maps: Final object-level concepts before classification.

### 7. Final Layers

- Global Average Pooling  $\rightarrow 1 \times 1 \times 1536$

- Dropout + Dense Layer → Softmax output (e.g., 100 for CIFAR-100 subset)

Feature maps: Fully condensed object understanding — one feature per class.